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SVR WIND PARAMETRS ESTIMATION: CASE OF MOHAMMEDIA – MOROCCO

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ABSTRACT

Wind energy is natural and renewable like solar energy; it is an inexhaustible source. Morocco, like many other countries in the world, is embarking on a new strategy aimed at improving its production of electricity from non-polluting sources. In this article, we aim to evaluate the wind potential in the region of Mohammedia by relying on statistical data of the wind, taken for several years. To achieve this goal, we use the famous law of Weibull. The distribution parameters are determined using new methods based on Support Vector Regression (SVR) method.

Keywords: Wind, Weibull, SVR, Estimation, Potential, Distribution.

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1. INTRODUCTION

The planet we live in is suffering from an unprecedented environmental crisis. Pollution caused by toxic waste and gases from around the world continues to destroy the ozone layer that protects us from solar rays. All of this requires that each of us, according to our position, participate in facing this scourge by finding viable and sustainable alternatives to save what is possible before it is too late. Aware of this danger, we strive to contribute with something, even so simple, in this great world project.

Wind is a movement of the atmosphere, the envelope that surrounds our planet, which forms when the air of a zone of high pressure moves towards a zone of low pressure. It is a natural phenomenon that preserves the qualities of the planet; it is clean energy.

Humans have been using this energy for millions of years. Wind is used to move boats, grind grain or pump water. This millennial technology is now used to produce electricity.

In recent years Morocco has seen a great movement in this direction. Several sites have emerged in several regions. Morocco has significant wind potential, particularly in the North, Northeast, and South:

- Essaouira, Tangier, and Tetouan with average annual speeds between 9.5 to 11 m / s at 40 meters.
- Tarfaya, Taza, and Dakhla with average annual speeds between 7.5 m / s to 9.5 m / s at 40 meters.

Our contribution concerns the city of Mohammedia, and we want to give an overview of the wind potential to help future investors in the field. All measurements are taken using an anemometer located at the height of 10 m. The site concerned is installed at ENSET and located by the following geographical coordinates:

- Latitude: 33°41′09″ North;
- Longitude: 7°22′58″ West;
- The altitude relative to sea level: 29 m.

In this paper, we rely on the famous law of Weibull to evaluate the potential of the wind in our site. It is a very flexible law and widely used in the field. The parameters of the law are estimated in the literature, as well as approximate graphical methods, as with very varied statistical methods [1] (least squares, the method of moments and the maximum likelihood method).

In the present work, a new method of identification of the parameters of Weibull's law is proposed. In the following, The Support Vector Regression method is detailed in the limit of our needs.

2. WEIBULL DISTRIBUTION

The distribution of Weibull is a law of probability making it possible to evaluate the wind potential of a site [2], [3]. In this paper, we are interested in the law with two coefficients c and k allow to characterize the wind on any site. The study is done on data collected by the laboratory for three years.

The coefficient c is the Weibull scale factor expressed in m/s. The coefficient k corresponds to the shape of the curve; it oscillates between 1 and 3. The smallest values of this coefficient correspond to a very narrow curve on the c value.

The probability density function and the cumulative probability function of the wind speed are respectively expressed by:

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} exp\left(-\left(\frac{v}{c}\right)^{k}\right) \quad (1)$$

$$F(v) = 1 - exp\left(-\left(\frac{v}{c}\right)^{k}\right) \quad (2)$$

The cumulative probability function (2) can be linearized as follows [4]:

$$Ln\left(1 - F(v)\right) = -\left(\frac{v}{c}\right)^{k}$$

$$Ln(-Ln\,(1 - F(v))) = kLn(v) - kLn(c)$$

$$\begin{cases} Y = Ln(-Ln\,(1 - F(v))) \\ X = Ln(v) \\ w = k \\ b = -kLn(c) \end{cases} \quad (3)$$

The corresponding linear law can be written:

$$Y = w * X + b \quad (4)$$

The constants w and b are determined by the SVR method, the parameters of the Weibull distribution are estimated by:

$$\begin{cases} k = w \\ c = e^{-\frac{b}{k}} \end{cases} \quad (5)$$

3. SUPPORT VECTOR RÉGRESSION

Support Vector Machines (SVMs) [5] focus on separating an example corpus into two classes, following their +1 or -1 labels. The regression consists in considering labels having any real value [6], and in trying to derive the function which the vector associates its label, from the examples of the corpus [7]-12].

We will study the case of a linear regression, which will be generalized to other regressions by the use of kernels instead of scalar products [13].

The regression presented assumes that a linear separator of the form (6):

$$f(x) = \langle w, x_i \rangle + b \quad (6)$$

$\langle w, x_i \rangle$ Is the scalar product

So, if the training data is well represented by the separator, a ε> 0 around the error, to achieve this objective, it is necessary to minimize the norm of the vector w.

$$\frac{1}{2}\|w\|^2 \quad (7)$$

Subject to:

$$\forall i, |\langle w, x_i \rangle + b - y_i| \le \epsilon$$

In practice, it is difficult to keep all the examples in a hyper-tube of width 2ϵ. We will express a function to optimize that allows certain examples to derogate from this constraint. The introduction of two relaxation variables (Slack variables): ξ_i and ξ_i' used to change the formulation of the problem in order to penalize the misclassified data. A cost parameter C> 0 establishes a compromise between the margin width, which has a regularizing role, and the number of misclassified samples. This new way of seeing the problem is called "soft margin". “Figure. 2“ illustrates this point.

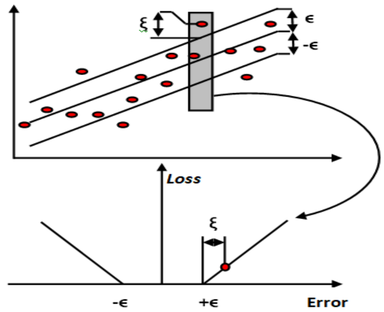

Figure 1 Error function.

The optimization problem for regression is to play on $\mathrm{w}, \mathrm{b}, \xi$ and ξ' to minimize [10]:

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i') \qquad (8)$$

Subject to:
$$\begin{Bmatrix} -\langle w, x_i\rangle - b + y_i \leq \epsilon + \xi_i \\ \langle w, x_i\rangle + b - y_i \leq \epsilon + \xi_i' \\ \xi_i * \xi_i' \geq 0 \end{Bmatrix}$$

Resolution

The optimization problem resolution is easier by passing to the dual problem, by the construction of the function Lagrangian (10). Let α_i and α_i' the multipliers relative to the first two constraints of the previous optimization problem, for more details consult [14].

The vector w of the separator is given by (9):

$$w_{\alpha,\alpha_i} = \sum_{i=1}^{n}(\alpha_i - \alpha_i') * x_i \qquad (9)$$

And the model is written (10):

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) * \langle x_i, x\rangle + b \qquad (10)$$

The bias parameter b can be calculated using the Karush-Kuhn-Tucker (KKT) conditions according to which the products between the dual variables and the constraints are null (11):

$$\begin{Bmatrix} \alpha_i(\epsilon + \xi_i + \langle w, x_i\rangle + b - y_i) = 0 \\ \alpha_i'(\epsilon + \xi_i' - \langle w, x_i\rangle - b + y_i) = 0 \\ (C - \alpha_i)\xi_i = 0 \\ (C - \alpha_i')\xi_i' = 0 \end{Bmatrix} \qquad (11)$$

For αi Є [0 C] $\xi_i = 0$,

From the first equation of (11) the bias b is evaluated by (12):

$$b = y_i - \langle w, x_i\rangle - \epsilon \qquad (12)$$

Non-linear case

Among the strongest motivations for the development of SVM for regression is their simple extension to nonlinear cases through the kernels use. Indeed, in a similar way to the classification case, we make a transformation of space Φ to be always faced with a linear regression. The inverse space transformation Φ^{-1}, allows returning to the original space after the resolution in the new space.

The transformation Φ and its inverse are realized thanks to a real function K(xi, xj) called Kernel. Equation (10) solution of the optimization problem is written (13):

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i') * k(x_i, x) + b \qquad (13)$$

Most commonly used kernel functions are [13]:

Linear kernel (14):

$$k(x_i, x) = (x_i^T * x + 1) \qquad (14)$$

Gaussian kernel (15) (radial basis function):

$$k(x_i, x) = e^{-\frac{\|x_i - x\|}{2\sigma^2}} \quad (15)$$

Polynomial kernel (16):

$$k(x_i, x) = (x_i^T * x + 1)^d \quad (16)$$

4. WIND POTENTIAL IN THE SITE

The wind speed used in the following represents the average of the maximum speeds taken every 24h, knowing that the wind speed is recorded every 15 minutes. As an indication, the wind speed variations in year 2013 are shown in figure 2.

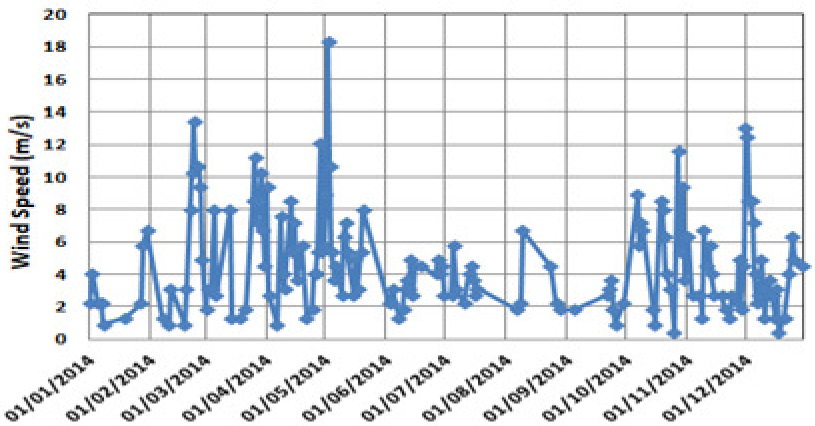

Figure 2 Wind speed variation in the considered site.

Figure 3 shows in three dimensions the monthly variation of the wind. In this graph we observe the minimum, maximum and average wind speed per month achieved in this site.

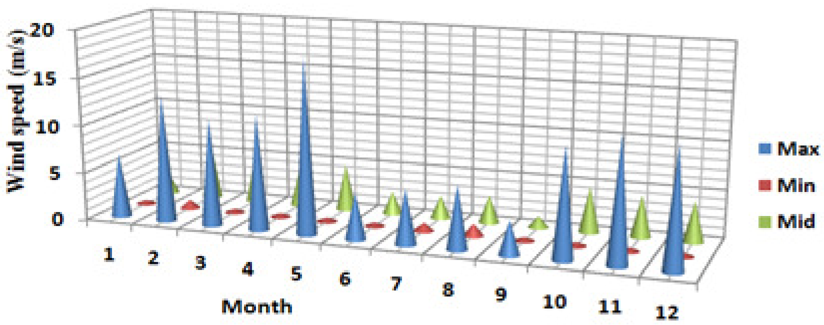

Figure 3 monthly variation of the wind speed

A script developed under Matlab allows importing the Excel data files to the Matlab workspace. Figure 4, figure 5 and figure 6 show a good linearity of the distribution. In the logarithmic scale, wind speed follows a linear law. The regression line SVR is well suited in this work.

The parameters w and b of the SVR regression line are determined by the relations (9), and (12). The Weibull probability coefficients are then determined by identification using the relations (4), (5) and (6).

$$\begin{cases} k = w \\ c = e^{-\frac{b}{k}} \end{cases} \quad (17)$$

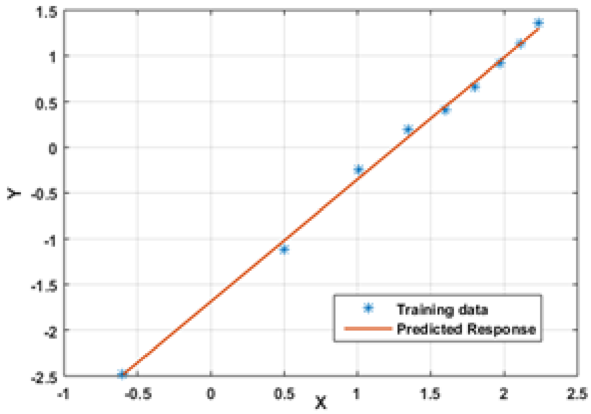

Figure 4 Logarithmic distribution, year 2013.

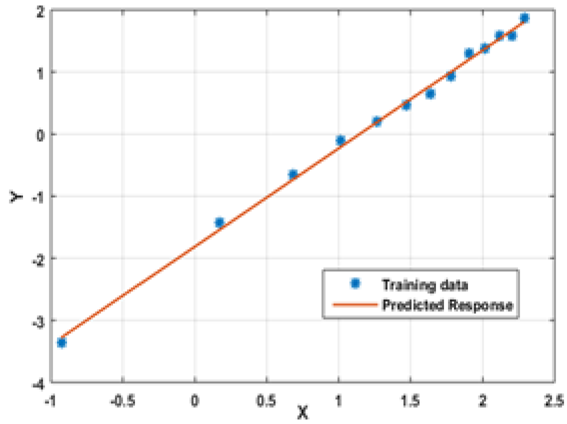

Figure 5 Logarithmic distribution, year 2014.

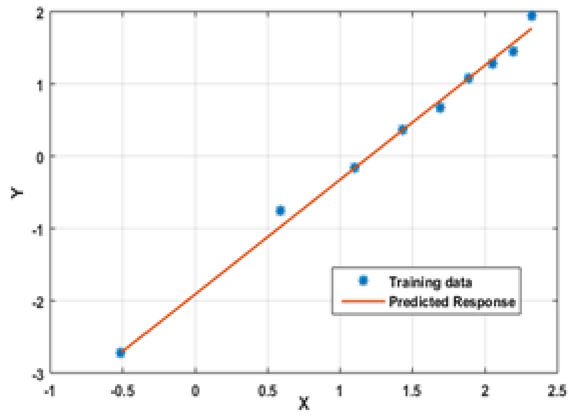

Figure 6 Logarithmic distribution, year 2015.

Table 1 summarizes the results obtained by year. Distribution parameters

Year	SVR parameters		Weibull parameters		wind average speed (m/s)
	w	b	c	K	
2013	1.3440	-1.6950	3.196	1.285	3.538
2014	1.5797	-1.8016	2.743	1.443	3,162
2015	1.5537	-1.8534	3.339	1.582	3,568

5. SIMULATION AND DISCUSSION

The following figures show, for three years, the distribution of the wind in the site located by the geographical data indicated above.

The probability density functions in figure 7, figure 9 and figure 11 vary very slightly over the three years (2013, 2014, and 2015). The overall average wind at an altitude of 10m is 3,365 m/s. Mean wind speed varies with altitude, empirical relationships allow for acceptable estimates [15].

The cumulative probability functions in figure 10 and figure 12 are similar, while the curve in figure 8 shows a small deviation.

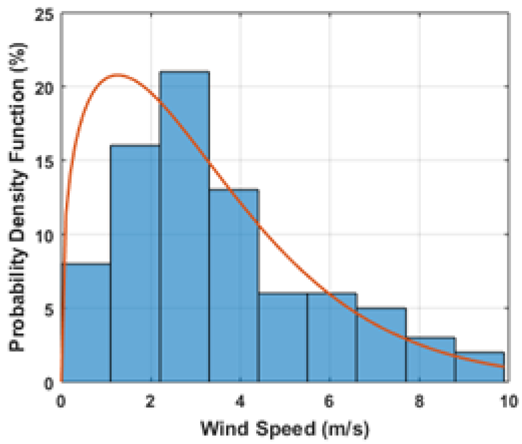

Figure7: Probability density function year 2013

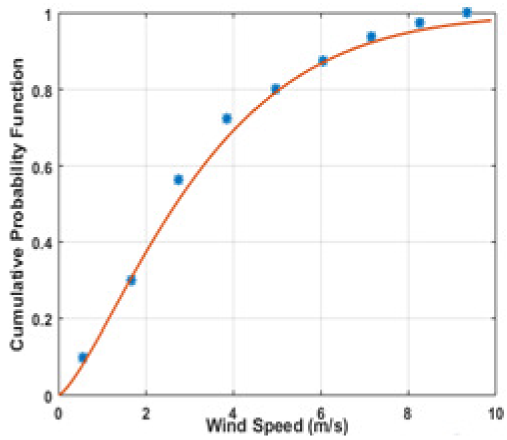

Figure 8: Cumulative probability functions year 2013

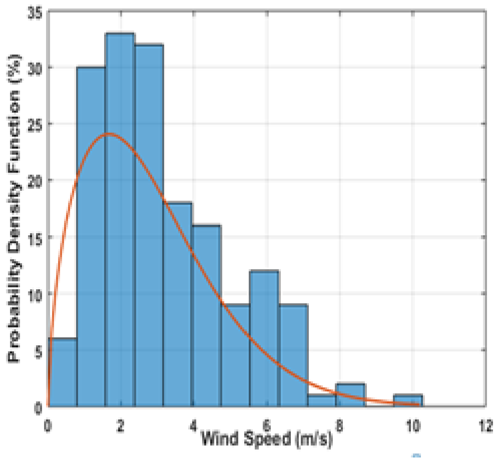

Figure 9: Probability density function year 2014

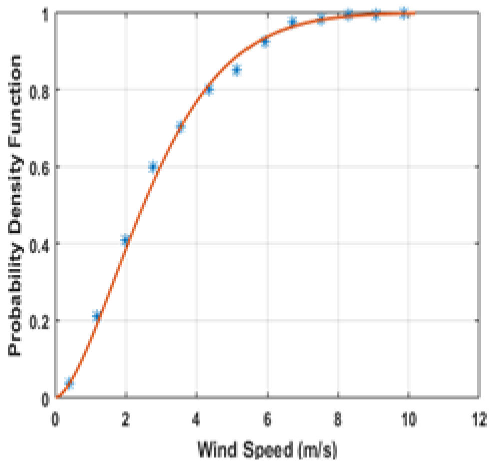

Figure 10: Cumulative probability functions year 2014

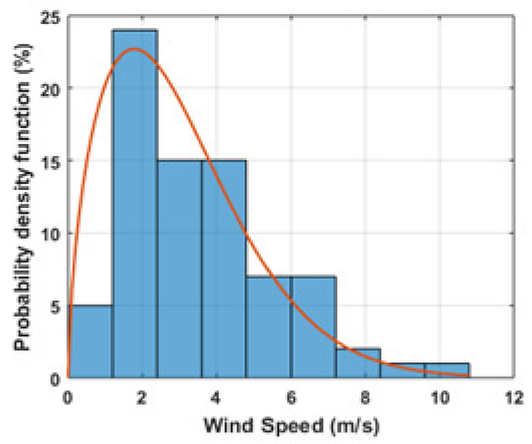

Figure 11: Probability density function year 2015

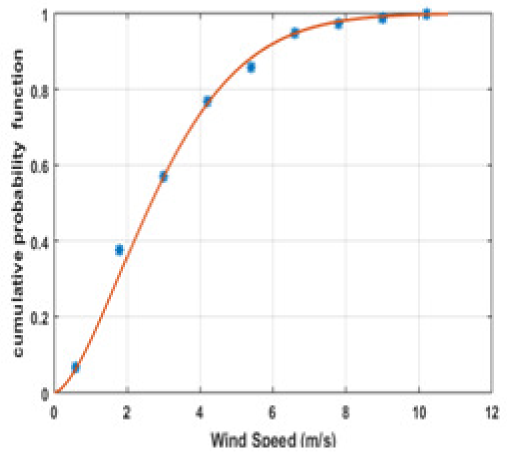

Figure 12: Cumulative probability functions year 2015

6. CONCLUSION AND PERSPECTIVES

This research aims at giving future investors in wind energy a clear idea about the Mohammedia region.

Optimization tools known for their robustness have been used to evaluate the parameters of wind distributions for three consecutive years.

A description of the tools was presented; the expected results show a great accuracy of the approach pursued.

A new infrastructure for transforming wind energy into electrical energy has just been installed. Future research focuses on the maintenance provisions to be considered, depending on the wind speed, to better optimize the life of our equipment. A maintenance method must be applied to the site, to achieve our goals.

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